Row Crop's Identification Through Hough Transform using Images Segmented by Robust Fuzzy Possibilistic C-Means

Christian Correa, Constantino Valero, and Pilar Barreiro

E.T.S.I. Agrónomos. Departamento de Ingeniería Rural
Universidad Politécnica de Madrid. LPF-TAGRALIA.
Av. Complutense s/n Madrid, Spain
c.correaf@alumnos.upm.es,{constantino.valero,pilar.barreiro}@upm.es
http://www.etsia.upm.es

Abstract. The Hough transform (HT) is a widely used method for line detection and recognition, due to its robustness. But its performance is strongly dependent on the applied segmentation technique. On the other hand, Fuzzy C-Means (FCM) has been widely used in image segmentation because it has a good performance in a large class of images. However, it is not good for noisy images, so that to overcome this weakness several modifications to FCM have been proposed, like Robust Fuzzy Possibilistic C-Means (RFPCM). In this paper, we propose to use the RFPCM algorithm for the segmentation of crops images in order to apply the HT to detect lines in row crops for navigation purposes. The proposed method gives better results compared with techniques based on visible spectral-index or Specific threshold-based approaches.

Keywords: FCM clustering, image segmentation

1 Introduction

Crop rows detection has a capital importance for the autonomous tractors guidance as well as in agricultural robots navigation, because give a path or an azimuth to follow. Several techniques have been developed to detect rows crops, but basically the idea is to segment the image, then over the binary image to detect borders, and finally to detect lines over the border image by the Hough transform.The Hough transform is widely used for line detection in images because is quite robust against noise, but have some limitations when the noise becomes important compared with the contrast of the objects and when lures are present in the images [6].

The first step of such applications is the segmentation of green vegetations, which presents several issues due to many factors, such as the shadows of the plant canopy and soil variability due to humidity and weeds.

The segmentation techniques used in this area can be separated in color-index-based segmentation, threshold-based segmentation and Learning-Based [3].

Color-index-based segmentation: In this technique the main idea is to generate a monochromatic image highlighting the difference between vegetation and soil, using for example the normalized difference index *(NDI=(G-R)/(G+R))* where R, G, and B are the color components of the RGB color space) [11], the excess green index (ExG=2-R-B), the excess red index (ExR=1.4 R-G), the color index of vegetation extraction *(CIVE=0.441R-0.811G+0.385B+18.78745)*[5], and the excess green minus excess red index *(ExG-ExR)* [7]. However one drawback of those techniques is that the index must be selected for the specific place/image where it will be applied.

Threshold-based segmentation: Several methods have been proposed such as the dynamic thresholding method, the Otsu-based method, the method based on the entropy of a histogram [14]. Those techniques have some problems, e.g. are mainly designed for monochromatic images, they assumes that the histogram of the image is bimodal, breaks down when the two classes are very unequal and does not work well with variable illumination.

Learning-Based: These techniques could be classified as supervised and unsupervised. Unsupervised including fuzzy clustering, for segmenting regions of interest from ExR and ExG[7]. In the supervised, the environmentally adaptive segmentation algorithm (EASA) for detecting plants [10] and the EASA under the HSI color space are examples of this techniques applied to deal with the light/shadows issue. Also based on the fact that the segmentation of green vegetations from a background can be treated as a two-class classification problem, the Fisher linear discriminant has been proposed as segmentation method [14]. Although, it should be noted that a two-class classification problem is not necessarily separable by a single line.

In this paper we propose to use a clustering method, called Robust Fuzzy Possibilistic C-Means Cluster algorithm (RFPCM)[13], to separate vegetation from soil or even different kinds of vegetation in order to detect lines of row crops using the Hough Transform (HT)[8].

RFPCM algorithm is suitable for this task because is noise tolerant and have low runtime requirements, and also have tendency to separate between two main clusters and noise.

2 Methodology

A set of different crop rows images (40) in the visible range RGB were selected randomly from Internet and processed using Matlab 7.11 running in a personal computer (Intel Core i7 980X Processor). The selection criterion was to select images with different, angles, illuminations, heights and backgrounds (with and without sky). The images resolution were from 800x600 to 320x240 in JPG format.

2.1 Images Processing

As a first step in the images processing, the images were transformed to L*a*b* color space in order to perform a human perceptual measure of the distance between pixels. In the L*a*b* color space the Euclidean distance between two points is approximately proportional to the perceptual difference between the two colors represented by these points. From this color space, channels a* and b* were selected, being a* its position between red/magenta and green, b* its position between yellow and blue. The channel L was eliminated in order to avoid the lighting/shadows effects.

As a second step, images were segmented applying Otsu's method for thresholding and then compared with thresholding levels generated by RFPCM algorithm using the same methodology as in Fuzzy C-Means Thresholding [2]. From the generated clusters by RFPCM algorithm, two thresholding levels were computed as follow:

$$Level_i = \frac{Max(a^*)_i - Min(a^*)_{(i+1)}}{2} \tag{1}$$

where, $i = (0, \ldots, c-1)$ and c is the clusters number, in our case, c=3.

As a third step, the level provided by the vegetation cluster was used to generate a binary image.

As a fourth step, over the binary image the following edge detection algorithms were applied, Sobel, Canny, Prewitt, Roberts, Zero Cross and Log[4].

As a fifth step, Hough Transform was performed over the edge's images generated in the previous step. Finally the best edges detection method was selected by visual inspection (the higher the number of crops row correctly identified, the better the method is). That is, which method detect a higher number of crop rows correctly.

As an alternative to the thresholding method, we propose take directly the cluster that corresponds to vegetation (generated in the step two by RFPCM) and using it as a binary image, skip to step four.

2.2 Robust Fuzzy Possibilistic C-Means Algorithm.

Despite the advantages of the L*a*b* color space, it has a drawback arising from the fact that the transformation from the RGB to the L*a*b* space is highly nonlinear. Nonlinearity transforms the homogeneous noise in the RGB space to inhomogeneous noise. This means that even if the RGB data are smoothed before the transformation, any small residual amount of noise may be significantly amplified[9]. To cope with this issue we selected Robust Fuzzy-Possibilistic C-Means algorithm [13], which is resistant to noise.

Suppose the data point $x_k \in R^s, k = 1, 2, \ldots, n$, is transformed from the original space to a feature space H with a kind of nonlinear mapping Φ, it becomes $\Phi(x_1), \Phi(x_2), \ldots, \Phi(x_n)$. So the inner product in the original space could be expressed by the Mercer kernel (2) [1], whith the Euclidean distance in the feature space shown in (3)

$$K(x_k, x_j) = (\Phi(x_k) \cdot \Phi(x_j)) \tag{2}$$

$$d_H(x,y) = \sqrt{\|\Phi(x) - \Phi(y)\|^2} = \sqrt{\Phi(x)\cdot\Phi(x) - 2\Phi(x)\cdot\Phi(y) + \Phi(y)\cdot\Phi(y)} \quad (3)$$

The objective function of the RFPCM algorithm is expressed as (4):

$$J_{m,\eta}(U,T,V) = 2\sum_{i=1}^{c}\sum_{k=1}^{n}(\mu_{ik}^{m} + t_{ik}^{\eta})\big(\|\Phi(x_k) - \Phi(v_i)\|^2\big) \quad (4)$$

where, c is the number of clusters, u_{ik} is membership of x_k to the ith cluster, v_i are the cluster centers, subject to $m > 1$, $\eta > 1$, $0 \leq u_{ik}, t_{ik} \leq 1$, $\sum_{i=1}^{c}\mu_{ik} = 1, \forall k$, $\sum_{k=1}^{n} t_{ik} = 1, \forall i$, with m and η are both weighting exponents. Combining (2) and (3), we can obtain:

$$\|\Phi(x_k) - \Phi(v_i)\|^2 = K(x_k,x_k) + K(v_i,v_i) - 2K(x_k,v_i) \quad (5)$$

Using the Gaussian function $K(x,y) = e^{-\|x-y\|^2/\sigma^2}$, as kernel, give $K(x_k,x_k) = 1$, $K(v_k,v_k) = 1$. Thus, the Equation (4) can be transformed into the following form through this kernelization:

$$J_{m,\eta}(U,T,V) = 2\sum_{i=1}^{c}\sum_{k=1}^{n}(\mu_{ik}^{m} + t_{ik}^{\eta})(1 - K(x_k,v_i)) \quad (6)$$

Under the same conditions of the Fuzzy Posibilistic C-Means algorithm (FPCM) [12], we will have the first order necessary conditions for extrema of $J_{m,\eta}(U,T,V)$ in terms of Lagrange multiplier theorem as follows.

$$u_{ik} = 1/\sum_{j=1}^{c}\left(\frac{1 - K(x_k,v_i)}{1 - K(x_k,v_j)}\right)^{1/m-1}, \forall i,k \quad (7)$$

$$t_{ik} = 1/\sum_{j=1}^{n}\left(\frac{1 - K(x_k,v_i)}{1 - K(x_j,v_i)}\right)^{1/m-1}, \forall i,k \quad (8)$$

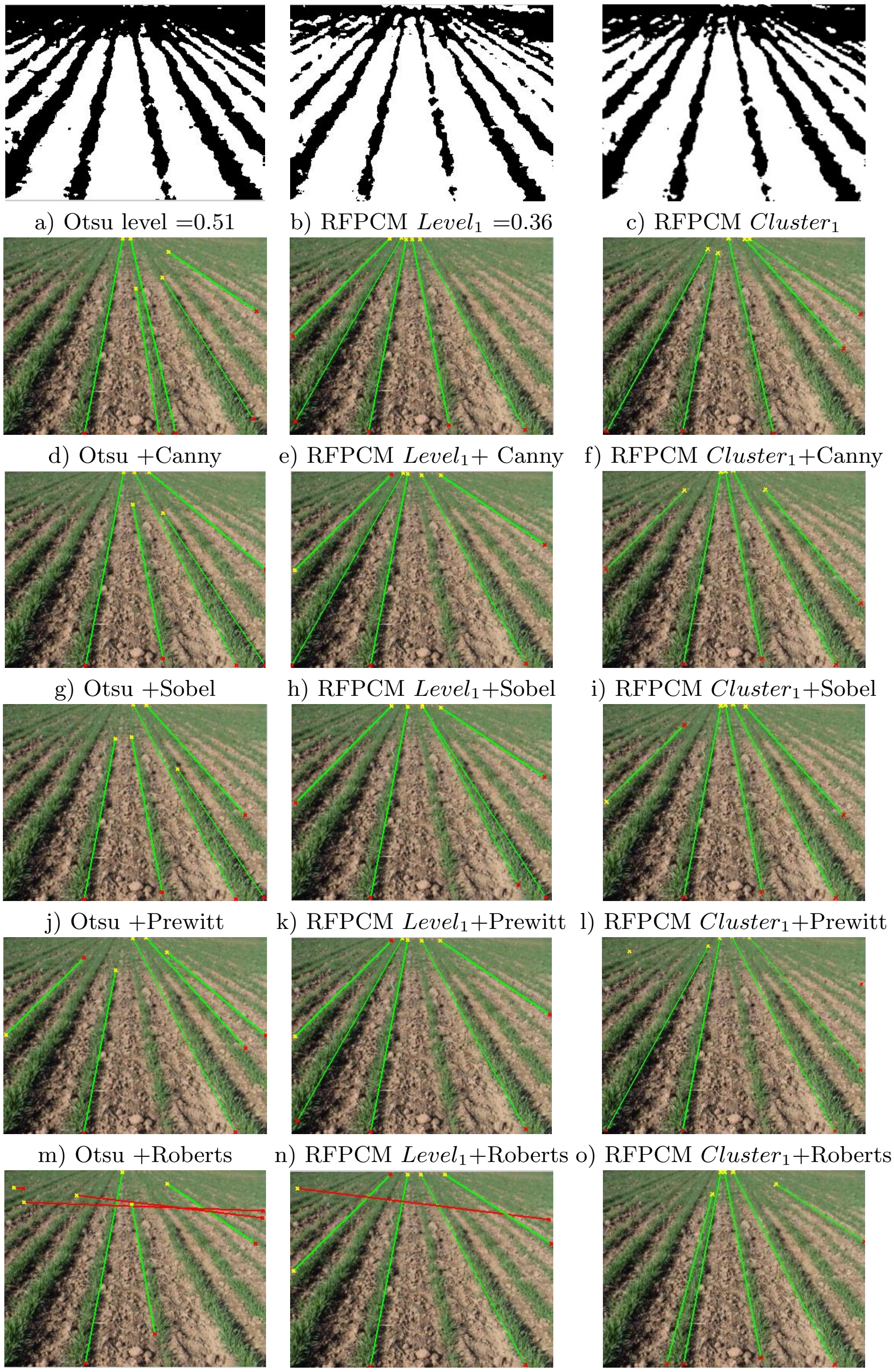
$$v_i = \frac{\sum_{k=1}^{n}(\mu_{ik}^{m} + t_{ik}^{\eta})\,K(x_k,v_i)x_k}{\sum_{k=1}^{n}(\mu_{ik}^{m} + t_{ik}^{\eta})\,K(x_k,v_i)}, \forall i \quad (9)$$

For our analysis we use 3 clusters, σ as the maximum between a^* and b^* channels ($m = 2$ and $\eta = 2$).

Finally, in order to assess the runtime performance of RFPCM this algorithm will be compared to the FCM runtime's. The rate between FCM/RFCM was performed using an image of 320x240 pixels.

3 Results

A comparative between Otsu's method and RFPCM levels applied over different edge detection algorithm are depicted in the Fig. 1. Although the Fig. 1 does not shows significant differences between methods, Sobel method systematically



a) Otsu level =0.51 b) RFPCM $Level_1$ =0.36 c) RFPCM $Cluster_1$

d) Otsu +Canny e) RFPCM $Level_1$+ Canny f) RFPCM $Cluster_1$+Canny

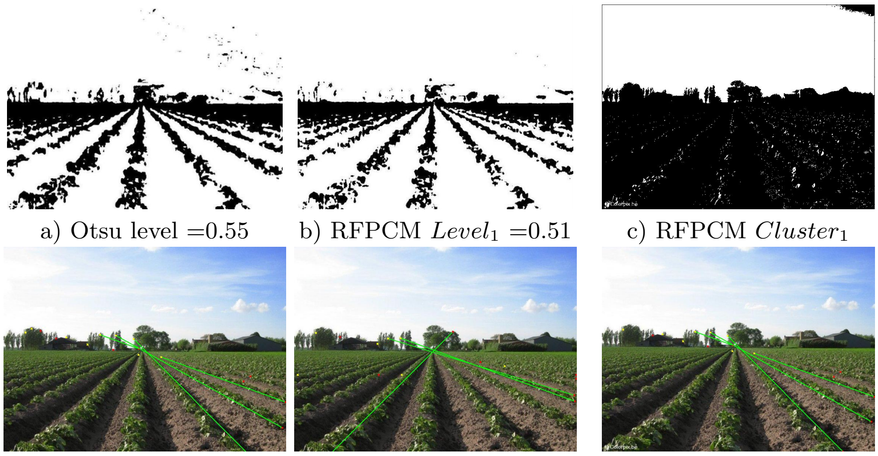
g) Otsu +Sobel h) RFPCM $Level_1$+Sobel i) RFPCM $Cluster_1$+Sobel

j) Otsu +Prewitt k) RFPCM $Level_1$+Prewitt l) RFPCM $Cluster_1$+Prewitt

m) Otsu +Roberts n) RFPCM $Level_1$+Roberts o) RFPCM $Cluster_1$+Roberts

p) Otsu +Log q) RFPCM $Level_1$+Log r) RFPCM $Cluster_1$+Log

Fig. 1. The binary images were generated by a) Otsu's method b) using thresholding levels computed from the RFPCM clusters, as depicted in (1). c) $Cluster_1$ taken directly from RFPCM. In every column bellow the binary images the results of the Hough transform after applied several techniques for edges detection. Detected lines with angles between 65° and 115° were drawn in green and the remaining drawn in red.



a) Otsu level =0.55 b) RFPCM $Level_1$ =0.51 c) RFPCM $Cluster_1$

d) Otsu +Sobel e) RFPCM $Level_1$+ Sobel f) RFPCM $Cluster_1$ +Sobel

Fig. 2. Image analysis of crop rows with sky and trees on the background. a) Binary images generated by Otsu's method b) Binary image generated using as thresholding level the $Level_1$ from (1) . In c) $Cluster_1$ taken directly from RFPCM and d), e) y f) the results of the Hough transform after applied Sobel edges detection.

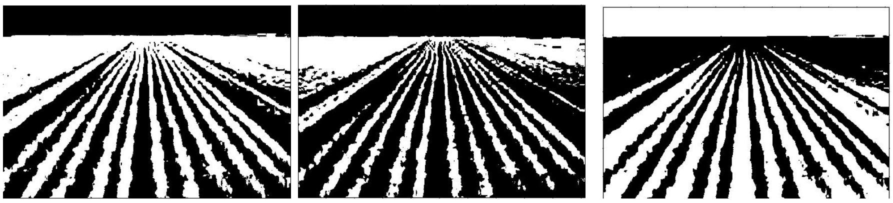
detected a greater number of lines and also tends to detect the central lines more often, which is desirable in guidance applications.

Figure 2 shows that Otsu's method misclassified regions of the sky and some lines are detected in the sky. Fig. 2 c) shows basically sky and ground separation, but some pixel remain from the crops, enough to allow detect three crop rows as shown Fig. 2 f). For a best visualization, detected lines with angles less than 65° and more than 115° are not displayed on the image.

When Sobel edge detections is applied over Otsu's method in a dry crop, the results in line detection is very poor as compared with Sobel applied over RFPCM *Level*. Sobel+Otsu detect one lateral line, while the best performance is given by Prewitt as shown at the Fig. 3 d), but when other edge detection methods are tested over RFPCM *Level* and RFPCM *Cluster*, the best result is given by Sobel as depicted in Fig. 3 e) and f). Unlike Otsu's method, RFPCM *Level* and direct cluster processing (RFPCM *Cluster*), always reach their best performance when are used in junction with Sobel.

A comparative between Otsu's method, thresholds generated by the RFPCM algorithm and direct cluster processing applied over a vineyard image is depicted in Fig. 4. Otsu's method misclassified almost the entire sky and also misclassified the mountains in the background put them in the vegetation cluster. However the Otsu's method is capable to detect a edge line on the vineyard.

The thresholding level provided by RFPCM showed a best classification performance, but generate a negligible misclassification of the mountain, which produce an additional line detection as depicted in Fig. 4 e).



a) Otsu level =0.44 b) RFPCM $Level_1$ =0.56 c) RFPCM $Cluster_1$

d) Otsu +Prewitt e) RFPCM $Level_1$+ Sobel f) RFPCM $Cluster_1$ +Sobel

Fig. 3. Image analysis of a dry crop. Due to the high threshold level given by RFPCM some lateral crop rows appear more weakly as compared with the Otsu's thresholding. For this reason RFPCM have a natural tendency to detect strongest crop's rows at the center of the images, as can see in the image e). RFPCM $Cluster_1$ +Sobel in f) shows the better performance by detecting five lines.

Table 1. Accuracy performance of the lines detection techniques as a percentage over entire line to be detected .

Method	Canny	Sobel	Prewitt	Roberts	Log	Mean
Otsu	50%	50%	50%	62.5%	37.5%	50%
RFPCM $Level_1$	62.5%	62.5%	50%	62.5%	50%	57.32%
RFPCM $Cluster_1$	62.5%	67.5%	62.5%	50%	50%	58.5%
Mean	58.3%	60%	51.17%	58.3%	45.8%	

Table 2. Accuracy performance of the lines detected on vineyard (worst case scenario).

Method	Canny	Sobel	Prewitt	Roberts	Log	Mean
Otsu	10%	5%	5%	40%	5%	13%
RFPCM $Level_1$	35%	40%	5%	65%	5%	31%
RFPCM $Cluster_1$	30%	35%	10%	60%	5%	28%
Mean	25%	26.6%	6.6%	55%	5%	

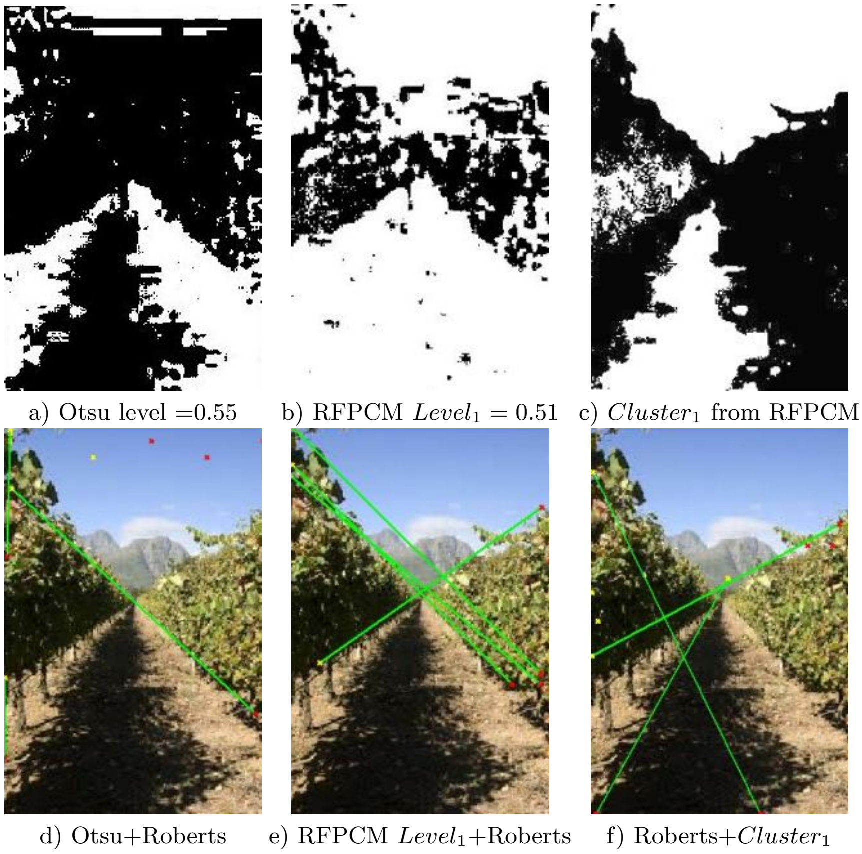


Fig. 4. Segmented vineyard image by three methods: a) Otsu. b) Level given by RF-PCM. c) Cluster taken directly from the vegetation (cluster generated by RFPCM without any kind of thresholding). d) Otsu + Roberts detect two vertical line and a few lines at the sky, which were deleted for a best visualization. Also detect a right one, but just one is not enough for our purposes. e) Detected lines by RFPCM $Level_1$+Roberts. This method misclassified some pixels of the mountain, which generates a wrong line detection. f) Roberts+$Cluster_1$ generated a wrong line detection, but give two correct lines detections.

On other the direct cluster processing generated a very poor classification because the shadows are considered as non vegetation, and the soil brand at the right is classified as vegetation as depicted in Fig. 4 f).

4 Discussion

Crop row detection, using as threshold the level generated by RFPCM clustering method, was performed and compared with the well known Otsu's method.

The results show that in the worst case scenario, that is, a vineyard image where strong shadows appear, plus mountains and sky, the proposed method based on thresholding by RFPCM clustering performs equal or better than Otsu's method.

On the other hand, the alternative method of direct cluster processing (RFPCM *Cluster*), is faster than the thresholding by RFPCM, because skips the thresholding step. However, for vineyard have a worst performance as compared to the thresholding by RFPCM.

Moreover, the proposed method doesn't use any kind of color's highlight(e.g. ExR, ExG etc.), so it can be adapted even on non green crops, for example on zero tillage fields or in early growing stages where soil color's predominant over the small plants area.

Sobel appear to be the best edge detection technique for lower crops, when our methodology was applying on vineyard images, Sobel is not the best choice because it find less lines as compared with Roberts, which gave the best performance independently of the thresholding methods applied.

The speed benchmarking between this technique using RFPCM *Level* and the classic Fuzzy C-Means Algorithm shows that the rate between the runtime of FCM/ RFPCM is four, so RFPCM *Level* is more suitable for real time applications (processing an image of 320x240 pixels takes 350ms).

Using as reference 350ms per image, a speed of 2.8 $m\ s^{-1}$ can be reached by processing 1 image per meter, enough for many agricultural tasks.

Finally these methodologies, in both case, RFPCM thresholding and direct cluster processing (RFPCM *Cluster*), have been shown to be robust against the noise, adaptable to the illuminations and to different crop's scenario, and enough fast to be implemented as a real time systems.

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